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# Negotiation Based Resource Allocation to Control Information Diffusion

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**Negotiation based resource allocation to control information diffusion**

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## DEDICATION

I would like to dedicate this work to my parents N. S. S. Sai and N. Sarada and my brother N. Sai Siddhartha and my sister-in-law Sri Divya for their love and support throughout my life. I wanted to thank Dr. Arun Natarajan for his invaluable moral support and guidance. I would like to thank my friends Tejaswini and Laharish who have been very supportive and encouraging. I would like to prostrate to Shri Sai Baba for this life and beyond.

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# ABSTRACT

Study of diffusion or propagation of information over a network of connected entities play a vital role in understanding and analyzing the impact of such diffusion, in particular, in the context of epidemiology, and social and market sciences. Typical concerns addressed by these studies are to control the diffusion such that influence is maximally (in case of opinion propagation) or minimally (in case of infectious disease) felt across the network. Controlling diffusion requires deployment of resources and often availability of resources are socio-economically constrained. In this context, we propose an agent-based framework for resource allocation, where agents operate in a cooperative environment and each agent is responsible for identifying and validating control strategies in a network under its control. The framework considers the presence of a central controller that is responsible for negotiating with the agents and allocate resources among the agents. Such assumptions replicates real-world scenarios, particularly in controlling infection spread, where the resources are distributed by a central agency (federal govt.) and the deployment of resources are managed by a local agency (state govt.).

If there exists an allocation that meets the requirements of all the agents, our framework is guaranteed to find one such allocation. While such allocation can be obtained in a blind search methods (such as checking the minimum number of resources required by each agent or by checking allocations between each pairs), we show that considering the responses from each agent and considering allocation among all the agents results in a negotiation based technique that converges to a solution faster than the brute force methods. We evaluated our framework using data publicly available from Stanford Network Analysis Project to simulate different types of networks for each agents.

# CHAPTER 1. INTRODUCTION

The study of propagation of information in a network of connected entities is an important area of research in multiple application domains ranging from epidemiology, social and market sciences to intrusion detection in computer science. The entities in the network can describe groups of hosts, populations, individuals or computer systems, while the corresponding information can be infectious diseases, opinions, fire or computer worms. The network itself describe how one entity can influence or can be influenced by others. It is important to understand and analyze the propagation of information to either contain the spread of information within desired level (e.g., in epidemiology) or maximize its impact (e.g., in marketing strategies). Most of the existing work is focused on the mathematical modeling of the behavior of the entities in the network and on analyzing the rate at which the external influences (e.g., immunizing the nodes, seeding with information) should be deployed to realize the desired results in the presence of information propagation.

Network is typically viewed as graph containing nodes and edges. Nodes represent entities in the network and edges represent some relationship between the nodes (Proximity, Friendship, Heredity, etc.). The basic step in understanding the impact of a spread of diseases, opinions, influences or computer viruses in a network involves understanding the behavior of population constituting the network. That is, one needs to analyze how the network expands and contracts if and when individuals or population groups join or leave the network. Such a study of networks led to development of random networks (Erdos and Renyi (1960)), small-world networks (Watts and Strogatz (1998); Barabasi and Albert (1999)), scale-free networks and their variants. The behavior of the networks is described in terms of the states, states being 'S' - the susceptible state of the entity, 'E' - exposed state of the entity, 'I'- the Infected state of entity and 'R' - the state of entity those recovered due to immunization or entity removed from the network due to death which is referred as SEIR model (Anderson and May (1979)). Other Variants being SI, SIR, SIS (Hsu and Hsieh (2005)). Another important aspect necessary for understanding how much of the network will be impacted due to information spread is the analysis of nature of spread. There are several models such as Independent Cascade model, Linear Threshold model etc., that capture information diffusion in the network (Shakarian et al. (2015)). In opinion propagation, the nature of spread can be analyzed by saying that an individual will be influenced by the opinion if majority of his/her friends hold the same opinion (Lerman and Ghosh (2010)) while in computer worm propagation, a host is affected by a worm if the worm moves from another host deemed to be "known" by the former host Gebhart (2004). We will use the terms infection and information interchangeably. We will also use spread and propagation interchangeably.

In epidemiology, the network of entities corresponds to population groups and their spatial/proximity relationships. Epidemiologists study the spread of the infectious diseases over such a network and classify them as outbreak, epidemic or pandemic based on severity and rate of the spread in the network (Eubank et al. (2004)). Existing research is focused on how the disease would spread in the given network and devise effective strategies to contain the spread (Do and Lee (2016)). We want to focus on the problem of resource allocation given a real-world epidemic scenario. Lets consider an example; there was an outbreak of Ebola in few West African countries Guinea, Sierra Leone, Liberia etc. Ebola being a deadly disease which can be out of control if no measures taken, epidemiologists wanted to study the disease to eradicate it. But the primary question here is, How do we distribute the vaccines among multiple countries or among multiple cities in the same country when government or private agencies have limited vaccines? To understand the emphasis on distribution of resources among multiple regions, consider a scenario where region A have same number of infections as in region B but A might handle the spread of infection better than B (because of better medical facilities or due to less density of population). So we focus on the problem of resource allocation where decision of distributing vaccines is handled by a central controller (government or central health organization) while agents (different cities or countries) get to choose where to place the vaccines using their own strategies.

With technological revolution in present days, information diffuses at very high rate which comes with its own pros and cons. In social/market sciences, the network captures the exchange of ideas and information among peers/leaders/followers. In Influence maximization problem (also referred as opinion propagation), sufficient set of nodes are identified that have maximal influence on spread of information. The objective is to maximize the spread by seeding information at the most influential node set, widely used in marketing strategies (Shafiq et al. (2013)). The contrast of maximization being Influence minimization problem, the spread of undesirable information or misinformation like rumors etc., is contained/suppressed by identifying the minimal set of links to be blocked. Especially during some major events such as elections, it is very critical to stop the spread of rumors as it might change the public opinion based on misinformation. This type of problem boils down to distribution of available resources to contain the spread of rumor at different regions.

While these are the examples of people/social networks, a technology networks such as Internet is a network of computer devices and the network and security experts analyze how the integrity of multiple networks are impacted by the propagation of worms. It may happen that when multiple networks are attacked, one of the many networks attacked is connected to military servers which cannot handle compromise of highly classified information while other network attacked is connected to internal servers which might handle the attack (consequences might be minimal) in a better way. The scenario becomes complex when there are less resources than required to combat the attack. It is important to analyze how the resources e.g. anti-virus can be distributed strategically when having some knowledge about networks attacked.

There are other types of real world problems like Power Grid, Fire Fighter etc., that can be modeled in a way similar to above mentioned scenarios. In Firefighter problem, various regions can be modeled as multiple networks where entities can represent a building and edges can represent the physical proximity (Finbow and Macgillivray (2007)). Protecting one of the region might prevent cascading fire to connected regions. When allocating resources, the objective must be to distribute fire fighters in a way that controls the spread of fire in all such regions while spread of fire is minimized in totality. Few scenarios that we face in our day to day activity can be modeled as a resource allocation problem to find a solution. For example, let's consider the problem of congestion in major cities like San Francisco in California and we might want to prevent the overflow of traffic at certain regions. It is often the case that patrols available to control such traffic, are limited in number. To find an allocation of patrols to different regions, the problem can be formulated as follows; every region can act as an agent where nodes represent the intersections of roads, edges represent the roads connecting the intersections and actual traffic flow is the information diffusing. Placing a patrol at a node prevents the node and its immediate neighbors from congestion. We need to find a strategy to distribute available patrols such that number of regions with congestion is minimal while leaving the decision of choosing where to place the patrols to the agents.

Given a network or multiple networks with possible infections, every region with infection can be considered to be controlled by an agent. If subgraphs or regions are connected (i.e. subgraphs from same network), we assume that agents are responsible for their respective neighborhood without considering the connectedness between the regions. Precisely, we consider the problem of resource allocation (resources can be vaccines, antivirus, generators, patrols) among multiple cooperative agents by a mediator negotiating until an optimal agreement is reached. Agents complete preferences/ requirements are not known to other agents and mediator. Based on the little information agents provide about their preferences, mediator distributes the resources among multiple agents. Leveraging this type of framework, only subspace of the entire solution space is visited. But the worst case would be to visit the entire solution space (Saha and Sen (2007)). Similar framework is being utilized in multiple domains such as, manufacturing and scheduling, network bandwidth allocation, space applications, crisis management etc., where multiple agents negotiate to reach to an agreement on resource allocation (Briola and Mascardi (2011)). There has been lot of investigation on multi-agent resource allocation problem and as a result many protocols have been established based on number of factors such as; the kind of resources (shareable, non-shareable, consumable, indivisible) being allocated, the type of allocation procedure, the reason behind the resource allocation (international crisis - social welfare, airline traffic management - avoid collisions, network bandwidth allocation - avoid congestion). We incorporate the ideology of mediator negotiating for resource allocation among multiple non-competing agents using our own mechanism for negotiation and simulating agents. Given a set of networks(act as agents) which needs resources to control information diffusion, we want to address whether globally available resources can be distributed such that every agent is successful in controlling information diffusion.

## 1.1 Challenges & Objectives

Difficulty in controlling the information diffusion is that control mechanisms are not available a prior. Existing work primarily focuses on the developing of control strategies for a given set of resources. The problem of resource allocation is challenging owing to the complexities and the size of the network. Exploring all possible strategies to distribute resources across multiple networks can be impractical in real time because of the run time overhead. This brings in a new challenge of resource allocation. Given a collection of regions controlled by agents, who are responsible for deciding whether or not a given set of vaccines/control measure is sufficient to address epidemics of disease/information in their respective network and if the agents cooperate, our objective is to find whether a central controller can effectively distribute vaccines to every such region.

## 1.2 Proposed framework

We propose a framework for utilizing the limited resources to control information diffusion in different networks. Given a collection of regions controlled by cooperative agents, who are responsible for deciding whether or not a given set of vaccines/control measure is sufficient to address epidemics of disease/information in their respective network, mediator is assigned the responsibility of distributing the available resources among agents and negotiating by iteratively considering the responses from the agents if required.

***Method***: We use an iterative resource allocation method controlled by a central controller (mediator) to distribute resources among multiple agents overseeing their neighborhoods Kyaw et al. (2013a). Agent provides little information based on the properties of their respective neighborhood. This way, controller has some information about the agents engaging in negotiating process. We allow only limited information exchange between the controller and agents

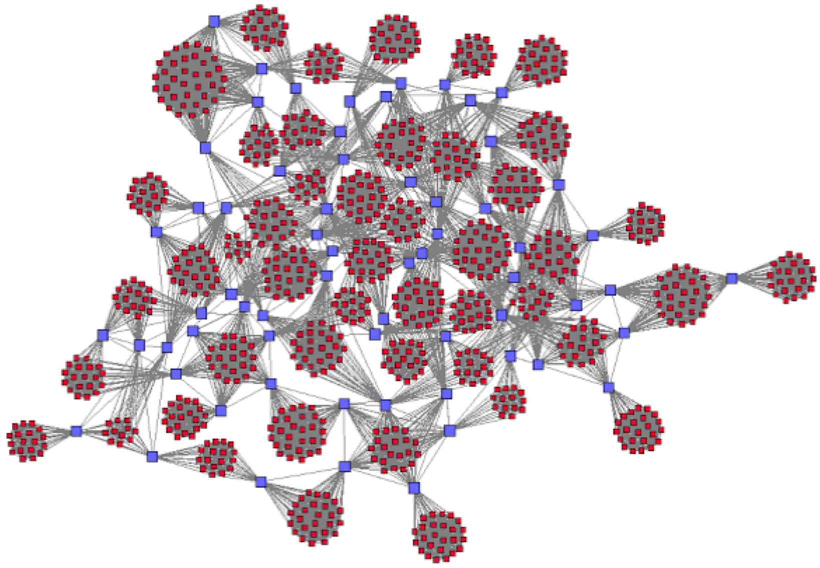


Figure 1.1: Example of multiple agents (Krebs (2010))

to maintain distributed nature of the control mechanism. Few given neighborhoods might be dense while others might be sparse. So blindly dividing the available resources equally might not be a good strategy in every case. In our methodology, controller leverage the information provided by each agent and based on the protocol, allocates resources. Once the resources are allocated to all the agents, every agent checks if the objective can be met. If any of the agents is not satisfied, then mediator tries to negotiate with the agents (here agents are cooperative rather than competitive) until a solution is found or it can be concluded that there exists no solution such that all the agents can be satisfied with available resources. For example, consider the Figure 1.1, there are multiple networks controlled by agents which needs resources to control the information diffusion. The goal of the central controller is to distribute the available resources such that every agent can successfully meet its requirement to control information spread.

## 1.3 Contribution

To summarize, following are the contributions of this work:

1. ***An agent-based negotiation strategy for effective allocation of vaccines to agents***

   The strategy is guaranteed to obtain a solution where each agent is satisfied with the allocation, if one exists. The strategy is iterative where in each iteration, new approximations of the solution are computed by taking into consideration responses from agents in the previous iterations. The strategy is particularly efficient in situations when the existence of the solution is altered by addition/removal of a small percentage of vaccines.

2. ***A framework for evaluating and validating the negotiation strategy***

   The framework can be used with different types of agent responses and can be used to compare against different iterative strategies for negotiations.

3. ***Applicability***

   The strategy is empirically evaluated by conducting experiments on different networks publilcly available in Stanford Network Analysis Project (Leskovec and Krevl (2014)). Experimental results reveal the feasibility and applicability of our framework to different real world networks.

## 1.4 Organization

The rest of the thesis is organized as follows. In Section 2, we talk about existing traditional approaches to control the information diffusion and existing applications of multi-agent controller based framework in different fields. In Section 3, we discuss our framework that helps us devise a strategy such that all the agents successfully control the information diffusion. We present the outline of the negotiation process using an illustrative example, and the agent's simulation algorithm . In Section 4, we present our experimental results performed on real world networks and comparison of our results to traditional approach (brute-force). In Section 5, we summarize our contributions, and discuss the possible extensions to this work.

# CHAPTER 2. REVIEW OF LITERATURE

Different aspects of the modeling and the analysis of information propagation over different types of networks have been studied. One line of research focuses on understanding the topological structure of the real world network. Another line of work focuses on understanding the nature of information propagation over the network. This is achieved by considering a network that closely represents a real-world distribution of entities and by running extensive simulations to mimic the spread of certain information (infectious diseases, opinions, rumors, computer worm, fire, traffic, attackers, etc.). Researchers further consider the problem of altering the spread, either to contain the spread or to maximize the impact of the spread; the objective is to find the rate at which the nodes in the network should be externally influenced (e.g., vaccinating nodes, deploying anti-virus, assigning patrol cars, firefighters, inserting or re-enforcing opinions). While the existing work focused on altering the spread either to maximize or minimize the impact of spread, we focus on the problem of allocating resources to multiple agents representing their respective neighborhoods. The basic assumption is that information is propagating in multiple localities where each locality is overlooked by an agent where multiple agents cooperate with each other (negotiate) to share resources and are typically controlled by a central controller with an objective to mitigate information diffusion. Agents can deploy different control strategies to mitigate the propagation. In this context, we discuss the contribution of existing work in controlling propagation and different network topologies and diffusion models (Section 2.1). Then we present an overview of the work that adapted multi-agent negotiation framework in various fields (Section 2.2).

## 2.1 Controlling Information Propagation

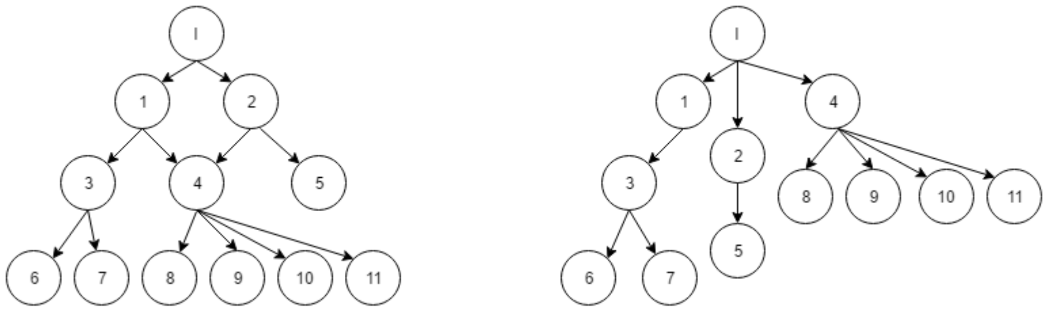
A network is a graph containing set of nodes and edges. Nodes represent entities in the network while edges represent the relationship (the reason behind the connection) between the nodes. Before deciding on the network topology and diffusion model, several questions such as; what will form the connections in the network? how much contact between the entities will lead to an infection spread in the network? are addressed by extensive research and simulations on real world models (Keeling and Eames (2005)).

To give a small overview about network topology: in random networks, every connection is formed at random. Each individual has fixed number of neighbors to which infection can propagate. In Lattice networks, entities are placed on a grid (generally in two dimensions) and edges are established between adjacent entities. This type of networks are mostly used in modeling the forest-fire networks. Lattice networks have high clustering and long path lengths while random networks lack clustering and have short path lengths. Small world networks are mixture of lattice and random networks, can be viewed as random connections added to a lattice network. Every node can be reached from most other nodes in the network. This type of networks are widely used in modeling epidemic networks. Scale-free networks are built by adding new entities and its connections preferably to entities which have large number of connections which imitates the social networks in real world. This type of networks are usually seen in World Wide Web networks, power grid networks, network of actor collaborations etc. Number of connections in this type of network takes power law distribution. Scale free networks depict heterogeneity while random networks, lattice networks, small world networks are homogeneous (Keeling and Eames (2005)).

There are a wide range of work employing techniques such as link removal (Marcelino and Kaiser (2009) , Tong et al. (2012)), merging infected nodes (Zhang and Prakash (2014)), blocking nodes (Briesemeister et al. (2003)), ranking based on eigen value (Tong et al. (2012)), choosing random nodes to vaccinate (Cohen et al. (2003)) etc., to control information propagation. Challenging factor is the size of the given real-world networks, they are often very large and finding an optimal solution will be a NP-Hard Problem in all such cases. Few studies were specific to networks such as scale-free networks while few are based on arbitrary networks. Dybiec et al. (2004) affirm that it is not possible to control the spread in scale free networks by preventive measures unless there are sufficiently many vaccines to treat large population. They also believe that it's not always possible to have complete information about how the disease spreads, sometimes the disease spreads from individual who is infected but undetected. In case of computer virus outbreak, reducing the connectivity between different internal networks can always be considered as an approach to prevent the epidemic but Briesemeister et al. (2003) believe that, it cannot be counted as a defense mechanism; there might be a case that attack has been realized long after it actually took place. Analysis on the network topology and the process of information diffusion plays an important role while devising a control strategy. For instance, Sapphire worms can exist only in Microsoft operating systems, hence eliminating devices with any other operating system will make the network smaller to handle.

(Zhang and Prakash (2014)) considered the problem of selecting k best nodes to immunize/quarantine in social/computer network when an infection is spreading. The goal is to find the best way to distribute available vaccines when disease is spreading. They assume that when nodes are immunized by vaccines, they are removed from the network itself. This type of questions can be similar to questions in other domains. For instance, in field of rumor propagation, one case ask which accounts in twitter must be disabled to discard a spam message? in field of computer networks, which computers or servers in the network should first be given the antivirus (in what order)? The problem is defined formally as *Given a graph G(V,E) where V represents the nodes and E represents the edges between the nodes, initial infected node set* $I_0$*, SIR model with propagation probability on each edge*$\{i,\ j\}_{p(i,j)} \in P$ *and curing probability* $\delta$*, and budget k (integer), find a set S of* $|k|$ *nodes from V to vaccinate to minimize expected total number of infected nodes during the spread of disease.*

Authors basic assumption is that given budget is not sufficient to vaccinate entire immediate neighborhood of infected nodes in $\mathrm{I}_0$. They proved that the problem defined above is a NP-hard problem. Generally graphs have submodular structure which leads to near to optimal solution but function used here is not submodular making it harder to approximate. The idea behind the proposed solution is that all the infected nodes are merged into a single super infected node.




(a) Original Graph (b) Dominator Tree

Figure 2.1: Example of dominator tree for a given graph

Because, in disease or virus or meme spread, what is important is, how are the non-infected (healthy) nodes are connected to infected nodes rather than how infected nodes are connected to each other. The merging is done as follows: if a node z has infected neighbors, u with edge weight (probability) $p_u$ and v with edge weight $p_v$, then new edge probability would be a logical OR of all individual probabilities i.e. 1-(1-$p_u$)(1-$p_v$). If the resultant graph $G'$ obtained after merging is a tree, then optimal solution can be obtained by calculating the benefit (essentially expected number of nodes to be saved after particular node is removed is referred to as benefit of that particular node) of every neighbor node of $I'$ and selecting top k nodes with highest benefit. If the resultant graph is not a tree, a dominator tree is obtained from the new graph $G'$. A node y dominates node x if every path from $I_0$ to x has y. Node y is immediate dominator of node x if every dominator of x (excluding y) dominates node y. Dominator tree is constructed by adding edges between nodes x and y if y is a dominator, using $I_0$ as root. Figure 2.1 is an example of dominator tree where if p = 1, then optimal solution is to vaccinate 4. We can see that finding optimal solution in dominator tree is quicker when compared to original graph.

While the authors Zhang and Prakash (2014) claim that this approach, is scalable to large networks (modeled as IC model and SIR model), can be applied to field of epidemics, social sciences (contain rumor spread), computer networks, and is 10 times better than other algorithms, Tong et al. (2012) makes a point expressing that deleting set of nodes to contain information diffusion might not be appropriate in all the cases. For instance, in social network, legitimate Facebook or Twitter accounts cannot be deleted to stop the rumor. Instead edge between nodes can be removed, meaning people can be unfriended if need arises. Now the problem boils down to finding the best k set of edges to be removed such that rumor propagation can be stopped. Kimura et al. (2008) also followed the theory of edge removal to address the problem of minimizing the undesirable (computer worm, rumor) information propagation. They also made a point about node vs edge removal techniques stating that *Blocking links between nodes that have high out degree is not always effective like in case with removal of nodes.*

Briesemeister et al. (2003) developed a framework to study the defensibility of computer network against malicious code/worms propagating by itself. This work has analyzed different aspects such as; the strategies that worms and viruses employ to spread infection in network (e.g., CodeRed propagated by identifying targets using random scanning), critical functionality of network etc., to devise a defense strategy. To simulate the control against attack, node level blocking of message exchanges between alerted applications was employed. Their insight after the study was that few scale free networks are inherently defensive. (Cohen et al. (2003)) deals with similar kind of objective but the immunization strategy is based on chosing small portion of random entities to be vaccinated. Tong et al. (2012) used eigenvalue to decide on which k edges must be removed. The smaller the eigenvalue, the better set of k edges to be removed to contain the spread of rumor or virus propagation in computer networks.

Kimura et al. (2008) modeled the network as an Independent cascade model, hence the diffusion happens according to edge probabilities. In most of existing works, networks are modeled as Independent cascade model. To give a quick idea about independent cascade model (IC model): The diffusion in IC model takes place in discrete time steps. Every state of the node can either be active or inactive and every edge is given a probability between 0 and 1. Every active node gets one chance to activate the neighbor node and succeeds with probability p associated between the active node and the neighbor node. If a node at time t+1 have multiple active neighbors at time t, then every node is given a chance in arbitrary order. This process terminates when there is no new node activated.

Kimura et al. (2008) formulated the problem formally as minimization problem: *Given an integer k, find a subset* $D'$ *such that* $|D'|=k$ *and* $c(G(D')) \leq c(G(D))$ *for any* $D \subset E$ *with* $D=|k|$. *G(D) is the graph obtained by removing the set of edges in D, c(G) is called contamination degree (average of influence degrees of all nodes in G).*

$$c(G) = \frac{1}{|V|} \sum_{v \in V} \sigma(v,G)$$

where $\sigma$(v,G) is expected number of activated nodes towards the end on IC model of G, also called influence degree of node v. Now finding the set of k edges to minimize c(G(D)) will lead to combinatorial explosion, hence approximation is used. The authors used an estimation method which is similar to bond percolation method to find the k best set of edges to be removed in the graph G.

Dybiec et al. (2004) conducted experiments on different topologies like small-world networks, scale-free networks, one-dimensional lattice etc., while Briesemeister et al. (2003) observed experiments on scale free networks and considered the network to be a SI model. Cohen et al. (2003) also demonstrated that strategy works well with scale-free networks such as movie-actors network, computer networks (email, World Wide Web, Internet) which have broad distribution of connections over the network.

Marcelino and Kaiser (2009) is a case study emphasizing on edge removal approach is better than blocking the nodes approach. Experiment was conducted on airline networks and results were as follows: selected airline cancellation is better than shutting down airport in totality, former took 81% longer to spread where there was 50% reduction in the latter case. Chen et al. (2010) expressed that while there are many strategies involving modeling the optimization problem as a game, few real world aspects are being missed such as node autonomy: on one hand finding socially optimal strategies is challenging, on other hand socially optimal strategy may not reflect individual entities decision of whether to get vaccinated/quarantined. Hence authors believe that such factors must be given weight and proposed an polynomial approximation algorithm of O(log n) which minimizes the total estimated cost (cost is associated with both entity being vaccinated and entity being infected).

There has been large epidemics in last decade, to name a few, rhizomania, citrus canker etc. Traditionally success of the control strategy is measure in terms of number of individuals affected by the disease or by number of individuals saved regardless of the cost. This would be prefect if the vaccination is cheap. But often in real-world scenarios, we should be able to control the spread of epidemic at moderate cost using limited available resources. Dybiec et al. (2004) aims to stop the spread of disease on networks at moderate cost using limited resources

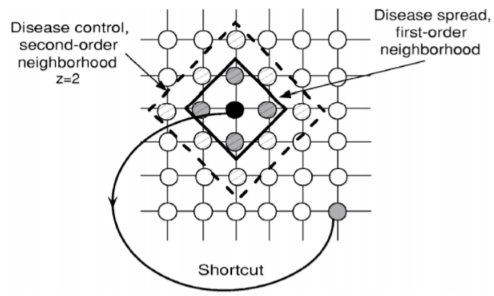



Figure 2.2: Example of Dybiec et al. (2004) Strategy

and local control strategies. By local strategies they mean that neighborhood centered around infectious node is considered while applying local methods to stop the disease spread. The basic assumption is that only limited knowledge of network is known which is only about the local links. For instance, consider the Figure 2.2, which represents a two-dimensional regular lattice networks where the infected node is in contact with four first order neighbors (immediate neighbors is referred as first order neighbors, neighbors of first order is referred as second order neighbors and so forth), eight second order neighbors and one shortcut edge. The disease spreads locally within first order neighbors and shortcuts, therefore individuals located within a fixed order z can be treated by control actions. But here the control strategy is efficient only when there is small neighborhood. Sometimes the disease spreads at faster rate and considering only the local neighborhood to control the spread might not work. Also this type of strategy is topology dependent. Another drawback is that efficiency of controlling the spread is dependent on choice of the radius (z).

Habiba et al. (2010) consider the problem of hindering the spread of rumors, misinformation, virus etc., in social or epidemic networks. This work focuses on dynamic nature of the network. For instance, questions like who has the information at current moment and which individuals are likely to get information in the next moment should be addressed. The strategy to eliminate the spread is based on number of graph properties (allocating weight to evolution of network at every time step). Few of such properties are listed below.

1. Degree of a node: number of neighbors of a node

2. Density: percentage of edges in the network

3. Dynamic Density: average density of network at each time step

4. Diameter: maximum length of the all the shortest paths

5. Temporal path: is a sequence of nodes $v_1$,$v_2$ ... $v_n$ where $(v_i,v_{i+1}) \in E_t$ for some t. Also for any i, j such that $i+1 < j$, and $v_i \in V_t$ and $v_j \in V_x$ then $t < x$. The length of the temporal path is equal to number of time steps

6. Betweeness: of a node is equal to sum of fractions of all the shortest path between this node and every other node in the network. This property depicts the position of particular node in the network

7. Dynamic Betweeness: of a node is fraction of all shortest temporal paths passing through this node. This property depicts the idea of capturing which individual has the information at current moment and which individual will receive it next

8. clustering coefficient: of an individual is the fraction of neighbors who are neighbors among themselves

9. Dynamic clustering coefficient: captures which entities are interacting among themselves in previous step.

While these are some measures listed, authors used 17 such measures to rank different nodes and selected top ranked nodes to vaccinate until the spread reduced to less than 10%. Experiments were explored on networks such as email communication of Enron cooperation, co-citations among scientists, co-location of individuals in a population, population of Grevy's Zebras etc.

## 2.2 Multi-Agent Resource Allocation

Negotiation is appropriate whenever we encounter a situation with conflict among multiple parties over any resource. Negotiation can be different types; competitive bargaining is where multiple parties tend to be self-interested and the process is viewed as a competition (its win or lose), positional bargaining is where parties tend to fix on a position and negotiate to reach an agreement essentially by compromising. Integrative bargaining is where agents try to cooperate and reach a win-win agreement such that all the parties are satisfied (Kyaw et al. (2013b)). multi-agent negotiation with shareable resources based framework is adopted in various fields ranging from international crisis management, grid computing, manufacturing and scheduling, network bandwidth allocation to space applications. Basic setting of the framework is as follows: There are multiple agents willing to cooperate either to mutually benefit each other or for cause of social welfare. Multiple agents are allocated resources based on negotiation protocol (can be in one or multiple steps) to reach a mutually optimal agreement. Agents can be competitive or cooperative and might have complete information or partial information about other agents. Resources can be consumable or non-consumable.

Chevaleyre et al. (2006) analyzed various aspects relating to multi-agent resource allocation environment to determine a protocol to adapt, such as, what is the purpose of resource allocation (social welfare, collision avoidance etc.)? What type of procedure is used to decide on allocation of resources? What type of resources are being distributed among agents (consumable or non-consumable, shared or cannot be shared, indivisible or divisible). Typically, the allocation procedure can be interpreted as centralized or distributed. In both the cases a single system is responsible for deciding on allocation of resources. The process of multi-agent negotiation can be viewed as an auctioneer trying to finalize the bids from different contractors. Authors defined the term multi-agent in distributed environment as *computational burden of finding an allocation is a responsibility shared among multiple agents.* If the goal(final outcome) is driven according to assessment of individual preferences, the allocation is computed depending on preferences of several agents (rather than individual preference). The objectives of such framework is either to find a feasible or optimal allocation of resources or both. For instance, goal can be either to find a feasible allocation of tasks to production units such that tasks are completed within the deadline or to find an optimal solution such that utility of every agent is as high as possible, or to find an optimal solution from set of feasible solutions (less distance, less conflicts) to avoid aircraft collisions.

The type of environment in multi-agent resource allocation framework can be divided into two categories. In one environment, agents do not have any or has some knowledge about other agents participating in the negotiation whereas in the second type of environment, agents have complete knowledge about other agents participating in the negotiation. It is easier to negotiate in the latter case as agents have complete knowledge, coming up with mutually beneficial agreements is undemanding. In Competitive (also referred as self-interested agents) environment, typically agents have complete knowledge about other agents, therefore studies focus on game theoretical modeling of the environment. In our framework, we assume the agents to be cooperative, hence we focus on protocols to allocate indivisible resources among multiple agents where agents do not complete knowledge about each other. There are few basic protocols such as:

1. **Strict Alteration**: In this protocol, every agent participating gets to pick one resource in every turn and agents is allowed to choose alternatively (Brams and Taylor (2000)).

2. **Balanced alteration**: In this protocol, the basic assumption is that the agents who gets to choose first have advantage over the other agent. So the second agent gets to choose in both second and third turns and so on. For instance, agent1 gets turns 1,4,5,8 ... and agent2 gets turns 2,3,6,7 ... to pick a resource. This protocol is devised to improve fairness (Brams and Taylor (2000)+.

3. **Contract-Net protocol**: In this protocol, one of the agents takes the role of manager and other agents act as contractors. For every task, manager advertises about the task and let agents bid for the task. Agents evaluate the task, to see if the task can be fulfilled with resources (time, hardware etc.,) and makes an offer accordingly. Depending on the bids, manager selects the most appropriate bid and assigns the task to agent who won. Manager monitors and reassigns the task if progress is not satisfactory (Davis and Smith (1988)).

4. **Exchange auctions**: This protocol is extension of Contract-Net protocol. In this protocol, the initial resource allocation is assumed to be given. Then agents come up with resources they are ready to exchange and other agents bid resources for exchange. The goal of this protocol is to reach a better allocation of resources (Saha and Sen (2007)).

In most of the works of multi-agent systems, average welfare of agents representing the society is taken as welfare of egalitarian society. Endriss et al. (2011) considers the multi-agent system as society of software agents with an objective to increase overall social welfare of such society. Initial assumption is that agents holds set of indivisible resources from total set of resources to which utility is assigned by each agent. This study emphasizes on egalitarian social welfare which brings the intuition of fairness (welfare is associated with welfare of weakest member of the society). Whereas the protocol in Kyaw et al. (2013b) is based on utilities (preferences) of individual agents. As Chevaleyre et al. (2006) discussed about the one of the factors that plays a vital role in deciding negotiation protocol is to analyze the purpose of resource allocation. Based on the requirements, protocols can be further classified. Approach proposed by Kyaw et al. (2013b) was simulated on well-known international conflict called Camp David that happened between Egypt and Israel and lasted for 13 days. United States acted as a mediator and initiated the negotiation process. Final agreement was reached after 6 rounds of negotiation on four different issues.

Saha and Sen (2007) proposed a three phase protocol to identify efficient allocation of resources. A bilateral environment is accustomed, meaning two agents would negotiate over resources (can also be extended to multilateral environment). To execute the first phase, they borrowed 'strict alteration' protocol fromBrams and Taylor (2000) and the outcome of the first phase would be the initial allocation of resources to agents. If no mutually optimal allocation can be reached (if no improvement mutually), then initial allocation would be the final allocation. Second phase involves generating a negotiation tree by agents participating. In this case, there are two agents, therefore the tree constructed is a binary tree. Maximum depth of the tree will be equivalent to number of resources in the negotiation process. Root node is denoted by zero, agent1 can create right child node and agent2 can create left child node. If no node can be created, then the process is terminated and initial allocation will be the final allocation. At any level, if one of the agents has utility less than its initial allocation utility, then further branches are not explored and the node is blacked out. Left child at level l will represent that resource l will be allocated to agent1 and similarly right child will indicate that resource will be allocated to agent2. When the tree is constructed, paths from root to

| | | |
|---|---|---|
| $u_1(\{\ \}) = 0$ | $u_2(\{\ \}) = 0$ | $u_3(\{\ \}) = 0$ |
| $u_1(\{r_1\}) = 5$ | $u_2(\{r_1\}) = 4$ | $u_3(\{r_1\}) = 2$ |
| $u_1(\{r_2\}) = 3$ | $u_2(\{r_2\}) = 2$ | $u_3(\{r_2\}) = 6$ |
| $u_1(\{r_1, r_2\}) = 8$ | $u_2(\{r_1, r_2\}) = 17$ | $u_3(\{r_1, r_2\}) = 7$ |

Figure 2.3: Scenario of agent's utility values for different allocation from Endriss et al. (2011)

each child node represent the allocation of a set of resources which would be the input to third phase. In third phase, an arbitrary agent, say agent1, will pick an allocation from the set obtained from second phase. Other agent removes all allocations such that utility of agent2 is less than that of utility of allocation proposed by agent1. Now agent2 proposes an allocation from the set and process is repeated until there is only one allocation in the set which would be the final allocation or no changes can be made to the set further. If there are many allocations after third phase, then one of the allocation is chosen randomly.

Authors conclude that the final outcome will be optimal allocation (there will be no outcome such that one of the agent's utility is greater than the one in final outcome). Few cons of this approach is that it takes longer time when resources are more than 100. Authors say that a solution is generated quickly when there are around 20 resources which is the case in most real-world scenarios.

This approach proposed by (Endriss et al. (2011)) is scalable to distributed environment. Allocation A is nothing but distribution of resources to set of agents. The utilitarian social welfare is defined as the sum of all utilities of agents in the process.

$$\mathrm{Sw}_u(\mathrm{A}) = \textstyle\sum_{i \in A} \mathrm{u}_i(\mathrm{A})$$

Egalitarian utility function is defined as follows:

$$\mathrm{Sw}_e(\mathrm{A}) = \min\{\ \mathrm{u}_i \mid \mathrm{i} \in \mathrm{A}\}$$

Allocations here are considered to be an ordered vector referred to as maxmin-ordering and allocation A′ is preferred over A if $\mathrm{Sw}_e(\mathrm{A}) < \mathrm{Sw}_e(\mathrm{A}')$. To create an ordering, concept of leximin-ordering is used. Let's consider an example in Figure 2.3. There are two resources to be distributed among three agents. Definitely there are allocations better than not allocating any of the resources to any of the agents. Allocating both the resources to agent2 has utility value 17. But the objective is to increase egalitarian social welfare, therefore this allocation would be ruled out. For instance, (0,0,17) < (0,2,5) where, in the latter allocation agent1 gets r1 and agent2 gets r2. (0,2,5) will not be the optimal allocation because assigning r2 to agent1 and r1 to agent2 will generate an ordered vector (0,3,4) which is better in terms of $sw_e$ value and is the final allocation.

In Kyaw et al. (2013b), the negotiation process is monitored by a mediator agreed upon by all the players. Mediator holds only partial information about all the players. Players present their preferences in form of CP-nets (directed graph annotated with qualitative conditional preference statements) to the mediator. Mediator then generates induced preference graphs (ordering of different allocation in form of a directed graph) for every player. Players have their own UCP-nets (utility values for CP-net). Mediator proposes a jointly optimal allocation depending on every player's UCP-net, players accept or reject it based on the values in their UCP-nets. Once the players provide their maximum preferred string, mediator tries to search for acceptable string for every player based on induced preference graphs. The negotiation process continues until a certain level in induced preference graphs is reached, which is when mediator declare that there is no possible jointly optimal solution.

We have seen above the examples of multi-agent resource allocation framework utilization in International Crisis Management and Egalitarian Social Welfare. Now we shall describe the framework's application in field of industrial engineering and collision avoidance. One of the domain where multi-agent negotiation is widely used is collision avoidance. One such example is unmanned aircraft routing protocols. To avoid collisions and find alternate routes, to know how much distance must be maintained, aircrafts need some kind of third party protocol which negotiates with every other aircraft in the system to reach an outcome. Šišlák et al. (2008) proposed an algorithm to handle airplane collisions (whenever there is a conflict). In this algorithm, assumption is that every agent (aircraft) can interact with those agents which are in certain range. In the case of conflict, all alternative routes are listed. If at all agents fail to find alternative routes, few parameters will be changed such as altitude, moving to left/right, speed, until an alternative route is found.

When current conflict is resolved, a check with other aircrafts is made to see if there are any other conflicts in the system. If yes then protocol is repeated for the first conflict in the list (first to occur w.r.t. time) of conflicts.

A similar problem was considered by Agogino and Tumer (2008), they adapted multi-agent negotiation system to solve the conflicts in airplane routing. In this work, they assume that entire airspace is divided into regions and further into sectors. Agents in this context are the ground location of the divided regions where agents own their respective sectors (responsible for the planes going through that sector). Every airplane has a flight plan which is essentially the a sequence of ground locations. Agent can change the flight plan in case of conflicts either by increasing the parameter holding the minimum distance maintained between different planes or by increasing the time on the ground (airports) or by changing the plane's path. Every agent in the conflict propose a set of solutions for the list of conflicts, best one is chosen using a learning algorithm.

Another application is in the domain of industrial applications where robots operate to complete assigned tasks avoiding collisions. Every agent is assumed to hold certain reserved area (can be negotiated) which is assigned using a protocol. Whenever a conflict occurs i.e. two agent's (robots) path to reach the destination collides, they communicate with each other and decide on who should change their paths based on the priorities. Change in path might involve changing the allocated reserved area or one of the agents might stop until other agent passes the reserved area. To avoid the possibility of indefinite delay, alternatives are detailed in Purwin et al. (2008).

To summarize about multi-agent resource allocation; Agents can be either cooperative or competitive. We have focused on existing work that have considered cooperative agents negotiating over resources. Agents can be in any form depending on the type of the problem. In Agogino and Tumer (2008), we can consider different airplanes as agents and resource being the flight plan which is a shareable and non-consumable resource. Agents negotiate over the flight plan if there exists a conflict. Mediator is the ground area where the conflict occurs and carries out and controls the negotiation. Similarly in Purwin et al. (2008), agents are nothing but set of robots and resources being the reserved area which is also shareable and non-consumable and also divisible. In this work, there is no external mediator, instead agents communicate with each other to negotiate. Work of Endriss et al. (2011) considers agents with utility values. The set of rules deciding which allocation is better can be seen as the negotiation protocol executed by the mediator. Agents do not know other agent's utility values i.e. agents do not know about other agents in the system.

In our work, we have accustomed similar framework where, objective is to control information diffusion in multiple regions, resources are the vaccines (can be any of antivrus, firefighter etc.,) that is to be distributed among multiple agents, overseeing their respective neighborhoods. A mediator controls the negotiation process and allocates resources based on information provided by agents (can be considered as utility values). Agents do not have any information about other agents. We present our work in detail in the next chapter.

# CHAPTER 3. A FRAMEWORK FOR RESOURCE ALLOCATION BASED ON NEGOTIATION

In this chapter, we describe our framework to distribute resources among multiple co-operative agents to control information diffusion. We utilize the concept of multiple agents negotiating over share-able resources to align with our objective to control information diffusion. We focus on the iterative negotiation protocol, executed by a central controller (referred to as mediator) to allocate resources. we assume that the network of entities modeled as a directed graph is given along with the nature of the spread through the entities. We also assume that agents are cooperative rather than competitive. Mediator has access to only partial information about agents. We aim to allocate resources using our framework leveraging the partial information provided by agents such that all the agents are satisfied. By end of the negotiation phase, if any one or more agents are not satisfied with given resources, we use the output of negotiation protocol as starting point for brute force method to find a strategy to allocate resources. We start by explaining high level architecture of our framework.

Figure 3.1 illustrates a block diagram of our framework. The input to our framework is multiple agents which essentially are graphs Graph 1, Graph 2, ... Graph n that has infection spreading and requires resources to mitigate information diffusion. Mediator consists of Competition module and Resource Allocation module. Once the resources are allocated to agents by the resource allocation module, agents simulate, and accordingly provide results and input to mediator if necessary. In this thesis, we have considered that agents simulate with an objective to control the spread within a threshold value equal to one forth of the size of its neighborhood i.e. with the given vaccines, number of infected nodes should not reach the given threshold value. Instead of mediator trying to distribute the given resources and find whether every agent can be satisfied, just providing the minimum number of resources needed

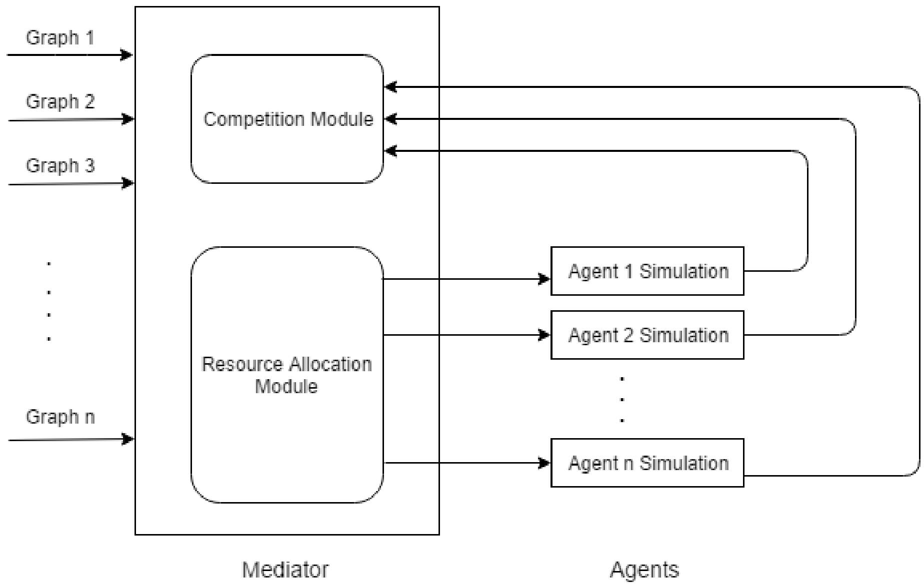



Figure 3.1: High Level Architecture

by every agent to the mediator will lead us to the optimal number of resources required but for every agent, to find the minimum number of resources requires many simulations and causes run-time overhead.

1. **Competition Module**: In this phase, agents provide partial information about their neighborhood, based on which, competition is held for various categories. Mediator keeps track of wins, losses and draws of every single agent. Typically, these wins, losses and draws depict the critical nature of the agents.

2. **Resource Allocation Module**: In this phase, allocation of resources is determined by the mediator based on result of competitions and the negotiation protocol.

3. **Agent Simulation Module**: Once resources are allocated in the previous phase, agents simulate to check whether the allocation will suffice their respective needs. For instance, if one of the agents $A_i$ has 100 nodes in the neighborhood, and is allocated with x vaccines, agent place the given vaccines using a randomized algorithm with an objective to control the diffusion with a threshold equal to half of size of its neighborhood that is 50.

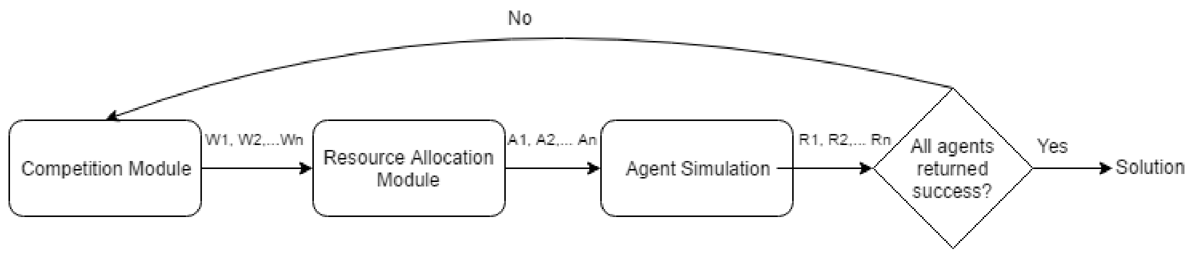



Figure 3.2: Flow of the proposed framework. Here W1, W2, ... Wn holds the number of competitions every agent won, and $A_1$, $A_2$, ... $A_n$, are the agents with resources allocated and $R_1$, $R_2$, ... $R_n$ represents the results returned by respective agents

**High Level Flow of the Proposed Framework:**

- Agents provide information to the mediator based on which mediator will initially allocates resources
- Agents run their simulations with given resources and provide the result to mediator
- Mediator executes the negotiation protocol to reassign the resources among agents and step 2 is repeated.

If every agent is successful (we make use of terminology success or failure to convey whether agent is satisfied or not satisfied respectively) then that particular distribution of resources is our desired output. Else agents provide information based on their most recent simulations to the mediator and the negotiation protocol is repeated by mediator using the new information provided (Figure 3.2 ). In few cases, this entire process might repeat forever until interrupted. We shall provide steps to determine oscillation and thus prevent it.

## 3.1 Mediator

In the framework, agents provide information that characterize the properties of their respective neighborhoods using these below three factors.

1. **Degree of Danger (DD)**: This factor depicts the danger degree in case the infection spreads above the threshold. For instance, in computer worm propagation problem, let one of the agents represent the network connected to confidential servers while the other agent represents the network connected to public servers. In this case, DD helps depict the critical nature of agents where DD will be higher for former network and relatively less for the latter.

2. **Degree of Influence (DI)**: This factor provides the maximum influence an entity has in the entire neighborhood. For example, in fire fighter's problem, if one of the agent have DI as 1000 and another agent have DI as 10. We might want to give preference to that entity which have 1000 nodes if there are insufficient fire fighters to distribute.

3. **Number of Critical Nodes (CN)**: This gives us the number of critical nodes in the agent neighborhood. There can be various definitions of the term critical node. We have considered that the median of all the DI of agents and measured the number of critical nodes by comparing it to the median. This factor helps the mediator know little about the structure of the agents in the negotiation process.

Note that, in our framework, agents do not have access to information about other agents. Mediator have access to whatever little information an agent provides. For example, in computer worm propagation problem, one of the agent is the network connected to confidential servers. But agent might want to keep this information in private, instead informs mediator that it is critical to protect its neighborhood through Degree of Danger factor. When agent calculates the number of critical nodes, mediator provides the agents with value of median as mediator has information about degree of influence of every agent. In this way agents only know that there is some kind of bound set for measuring critical nodes but do not know individual agent's degree of influence information.

### 3.1.1 Competitions

For each of aspect provided by the agent, a competition will be held between every pair of agents by the mediator. Mediator keeps track of number of wins and draws for every agent. To

Table 3.1: Agent Information at Round 1

| Agents | DD | DI | CN |
|---|---|---|---|
| A1 | 200 | 90 | 2 |
| A2 | 400 | 100 | 5 |
| A3 | 350 | 150 | 5 |
| A4 | 120 | 60 | 0 |
| A5 | 300 | 90 | 3 |

better understand our methodology, let's consider an example. Suppose there are five agents $A_1$, $A_2$, $A_3$, $A_4$, $A_5$ and Table 3.1 holds the initial DD, DI and CN information of respective agents.

CN is calculated as follows; Median of 60, 90, 90, 100, 150 is 90, Hence CN is the number of nodes whose degree (number of connections) is greater than 90. For every individual aspect, number of competitions held is $5C_2 = 10$ which basically is the number of unique pairs possible for five agents i.e. competition will be held between ($A_1$, $A_2$) ($A_1$, $A_3$) ($A_1$, $A_4$) ($A_1$, $A_5$) ($A_2$, $A_3$) ($A_2$, $A_4$) ($A_2$, $A_5$) ($A_3$, $A_4$) ($A_3$, $A_5$) ($A_4$, $A_5$). There are three factors in total, therefore total number of competitions is 30. $A_2$ has greater DD than $A_1$, $A_3$, $A_4$, and $A_5$, greater DI than $A_1$, $A_3$, and $A_5$, greater CN than $A_1$, $A_4$, and $A_5$. Therefore, number of wins for $A_2$ is 10. Similarly, number of wins for every agent is calculated:

$$A_1\text{: } 3 \ A_2\text{: } 10 \ A_3\text{: } 10 \ A_4\text{: } 0 \ A_5\text{: } 5$$

Observe that competition ($A_1$, $A_5$) is a draw for aspect DI and ($A_2$, $A_3$) is a draw for aspect CN.

Number of draws = 2

### 3.1.2 Resource Allocation by Negotiation

We now describe our negotiation protocol for allocating resources. To start with the initial allocation, few vaccines will be distributed equally (say x) and remaining vaccines (say y) will be distributed according to the results of competition.

Result vector of agents, that stores the agent's results is maintained by mediator and is initiated to [failure failure failure failure failure].

$$\text{Number of vaccines to distribute equally} = \text{total vaccines} \times \text{factor}$$

Initially factor is set to $\frac{1}{2}$. Let the total number of vaccines be 300. In this example, half of total vaccines, which is equal to 150, will be distributed equally among all the agents and the remaining 150 vaccines will be allocated according to the results of the competition.

**Round 1**:

Step1: According to the results of the competition, an agent $A_i$ will get:

$$A_i = \frac{number\ of\ wins\ of\ A_i}{total\ competitions} \times \text{y vaccines}$$

Hence allocation is as follows after step 1:

$A_1$ will be allocated $\frac{3}{30} \times 150 = 15$ vaccines

$A_2$ will be allocated $\frac{10}{30} \times 150 = 50$ vaccines

$A_3$ will be allocated $\frac{10}{30} \times 150 = 50$ vaccines

$A_4$ will be allocated $\frac{0}{30} \times 150 = 0$ vaccines

$A_5$ will be allocated $\frac{5}{30} \times 150 = 25$ vaccines

Step2: There are 2 draws out of 30 competitions, this portion of vaccines will be added to number of vaccines to be equally distributed.

Number of vaccines to be equally distributed $= \text{x} + \frac{number\ of\ draws}{total\ competitions} \times \text{y}$ vaccines

Number of vaccines to be equally distributed$= 150 + \frac{2}{30} \times 150 = 150 + 10 = 160$

There are five agents, as a result every agent will be allocated with $\frac{160}{5} = 32$ vaccines along with the allocation in previous step. Resource allocation after round 1 is given in Table 3.2.

Now, agents will simulate with given resources and provides the results which can be one of success or failure, to the mediator. Previous Result vector can change in one of the following possibilities:

1. Count of success in the result vector can increase

2. Count of success in the result vector can decrease

3. Count of success in the result vector can remain the same

Table 3.2: Resource Allocation after Round 1

| Agents | Step 1 | Step 2 | Allocation |
|---|---|---|---|
| A1 | 15 | 32 | 47 |
| A2 | 50 | 32 | 82 |
| A3 | 50 | 32 | 82 |
| A4 | 0 | 32 | 32 |
| A5 | 25 | 32 | 57 |

Depending on one of the three outcomes, mediator will negotiate according to negotiation algorithm:

1. If count of success decreases or remains the same then factor $= \frac{factor}{2}$
2. for agent's who returned success, consider their wins as draws in the next round

**Round 2**:

In our example, let's say the result vector after round 1 is [success failure success success failure] i.e. with the allocation in first round, $A_2$ and $A_5$ were not satisfied (failed to control infection spread) and $A_1$, $A_3$, $A_4$ were satisfied. Count of success in result vector have increased and therefore, wins of agents $A_1$, $A_3$, $A_4$ will be considered as draws in the next round of competitions. Agents will again send their DI and CN (Table 3.3), calculated based on the nodes visited during the simulation phase, to the mediator. DD of agents will remain the same throughout the process. For example, let's say agent $A_3$ has vaccinated nodes $n_6$, $n_9$, $n_{46}$, $n_{68}$, in round 1. $A_3$ will set DI value as the highest number of connections a node has, in the set $\{n_6, n_9, n_{46}, n_{68}\}$ holds. Number of wins for agents is:

$$A_1\text{: } 6 \ A_2\text{: } 11 \ A_3\text{: } 3 \ A_4\text{: } 1 \ A_5\text{: } 8$$

Step1: Allocation according to competition results

$A_2$ will be allocated $\frac{11}{30} \times 150 = 55$ vaccines

$A_5$ will be allocated $\frac{8}{30} \times 150 = 40$ vaccines

Number of draws $= 1 + A_1$ wins $+ A_3$ wins $+ A_4$ wins

Number of draws $= 1 + 6 + 3 + 1 = 11$

Table 3.3: Agent Information at Round 2

| Agents | DD | DI | CN |
|---|---|---|---|
| A1 | 200 | 90 | 2 |
| A2 | 400 | 100 | 5 |
| A3 | 350 | 50 | 0 |
| A4 | 120 | 60 | 0 |
| A5 | 300 | 80 | 8 |

Table 3.4: Resource Allocation after Round 2

| Agents | Step 1 | Step 2 | Allocation |
|---|---|---|---|
| A1 | 0 | 41 | 41 |
| A2 | 55 | 41 | 96 |
| A3 | 0 | 41 | 41 |
| A4 | 0 | 41 | 41 |
| A5 | 40 | 41 | 81 |

Step2: Number of vaccines to equally distribute $= 150 + \frac{11}{30} \times 150 = 150 + 55 = 205$

Resource allocation after round 2 is given in Table 3.4.

**Round 3**:

Let's say the result vector after round 2 is [failure failure success success success]. Count of success in result vector is the same, therefore, factor is reduced by 1/2 and wins of agents $A_3$, $A_4$, $A_5$ will be considered as draws in the next round of competitions. Agents will provide their DI and CN once again (Table 3.5).

Number of vaccines to equally distribute = total vaccines $\times$ factor

Number of vaccines to equally distribute, x $= \frac{300}{4} = 75$

Remaining vaccines y $= 300 - 75 = 225$

Number of wins for agents is:

$$A_1\text{: } 5 \; A_2\text{: } 9 \; A_3\text{: } 11 \; A_4\text{: } 0 \; A_5\text{: } 3$$

Step1: Allocation according to competition results

$A_1$ will be allocated $5/30 * 225 = 37$ vaccines

Table 3.5: Agent Information at Round 3

| Agents | DD | DI | CN |
|---|---|---|---|
| A1 | 200 | 90 | 2 |
| A2 | 400 | 100 | 2 |
| A3 | 350 | 150 | 3 |
| A4 | 120 | 60 | 0 |
| A5 | 300 | 80 | 0 |

Table 3.6: Resource Allocation after Round 3

| Agents | Step 1 | Step 2 | Allocation |
|---|---|---|---|
| A1 | 37 | 39 | 76 |
| A2 | 67 | 39 | 106 |
| A3 | 0 | 39 | 39 |
| A4 | 0 | 39 | 39 |
| A5 | 0 | 39 | 39 |

$A_2$ will be allocated 9/30 * 225 = 67 vaccines

Number of draws = 2 + $A_3$ wins + $A_4$ wins + $A_5$ wins

Number of draws = 2 + 11 + 0 + 3 = 16

Step2: Number of vaccines to equally distribute = $75 + \frac{16}{30} \times 225 = 195$

Resource allocation after round 3 is given in Table 3.6.

This process is terminated when one of the following condition is met

1. when all the agents are satisfied, in other words count of success in result vector is equal to number of agents, which is our desired solution.

2. when count of success in the result vector is same as previous step and if same set of agents returned success and the number of vaccines to be distributed equally is the same as previous step, then its likely to oscillate, hence terminate. For example, in the above problem considered, if the result of allocation is [success failure success success failure], wins of A1, A3, A4 will be considered as draws and if the number of vaccines to distribute equally is 205, then its likely to oscillate.

If the negotiation phase terminates because of the second condition, then a brute force method is accompanied. We execute a binary search between every pair of agents which returned success and failure. The idea behind using pair-wise binary search is that few agents which returned success might hold vaccines more than required to control the spread, hence such extra vaccines can be used in other neighborhoods. As we have considered the environment to be cooperative, these agents lend to agents which needs more vaccines to meet the objective. If the outcome of this method is negative, then we output that there exists no solution i.e. there is no resource allocation such that all the agents can be satisfied. Otherwise the outcome of this method will be our final allocation. We evaluated our framework against brute force method and results are presented in the next chapter.

## 3.2 Agent Simulation

To validate our framework, we have accompanied randomization based approach to simulate agents which we shall detail in this section. We have considered the network to be a SIR model. Initially the state of all entities is susceptible except for those given initial infected nodes. When vaccines are allocated to agents, every agent tries to place the vaccines in its neighborhood such that spread of infection controlled. To model the fact that not all vaccines allocated are available at the moment, we assume that along with assignment of vaccines, value of per-step-vaccine parameter is also given which essentially tells us the number of vaccines that can be used at every time step out of total assigned vaccines. The value of per-step-vaccine should be atleast 1. Once vaccinated, an entity cannot be infected again. Here we consider the time to be discrete. Hence, at every time step, infection spreads to all the immediate neighbors except for the nodes which are vaccinated from those nodes which are infected in previous time step.

Each agent simulates using the Algorithm 1 which is continued until all the vaccines are used or until all the nodes are either vaccinated or infected. If the agent succeeds in controlling the information diffusion before number of infected nodes reaches the threshold value, then agent keeps track of this vaccination strategy (which nodes are vaccinated and which nodes are infected in particular simulation) and returns success. Otherwise i.e. if the threshold is reached,

**Algorithm 1** Algorithm for Agent Simulation

```
procedure AGENT SIMULATION
    count ← 0
    for i 1 to numberofvaccines do
        for each node v in the neighborhood do
            generate a random number between 1 and 10000
            if random number > 5000 then
                vaccinate node v
                count + +
            end if
            if count == perStepVaccine then
                count ← 0
            end if
        end for
    end for
end procedure
```

agent returns failure. Agents remembers the history particularly about the allocation to which it returned success. Once vaccines are allocated, agents check whether current allocated vaccines is equal or greater than the one seen previously, if yes then agents retrieves the vaccination strategy from the history as current vaccination strategy and returns success.

In this way, a solution, such that every agent is satisfied with allocated vaccines is arrived, if one exists or the framework outputs that there exists no satisfiable solution. A comparison between proposed method and brute force method to distribute vaccines is presented in the next chapter. In brute force method, available vaccines are distributed equally at initial step and a pair-wise binary search is performed between satisfied and not satisfied agents until a solution is found.

# CHAPTER 4. EXPERIMENTAL EVALUATION

## 4.1 Experimental setup

In our framework, each region is represented by a network of entities. For the purpose of experimental evaluation, we have developed a simple simulation based technique and assumed one infection/region to replicate how an agent will evaluate the effectiveness of allotted vaccines. We have conducted experiments widely on web-graph of Google where nodes represent webpages and edges represent the hyperlink borrowed from Leskovec and Krevl (2014). Input to our framework is the network, number of infections which typically is the number of agents, size of the agents that decides how big agent's neighborhood should be generated, number of vaccines in total, number of vaccines per time step and number of simulations for agents to run. Figure 4.1 outlines how we have generated multiple agents from given input network. We consider that there is no intersection of nodes in the neighborhood of the agents. Size of N agents is given as input. It is assumed that the objective is to control the infection spread within the threshold where threshold is defined as one fourth of the size of the agents i.e. the number of infected nodes should not reach the threshold given the number of time steps. To evaluate the performance of our framework, we have conducted experiments using two different methods and compared the time taken to find a resource allocation. The first method is the Negotiation-based resource allocation and the second method is brute-force method. In brute-force method, given vaccines are equally distributed among all the agents in the first round. Then a pair wise binary search is accompanied between the agents satisfied and unsatisfied.

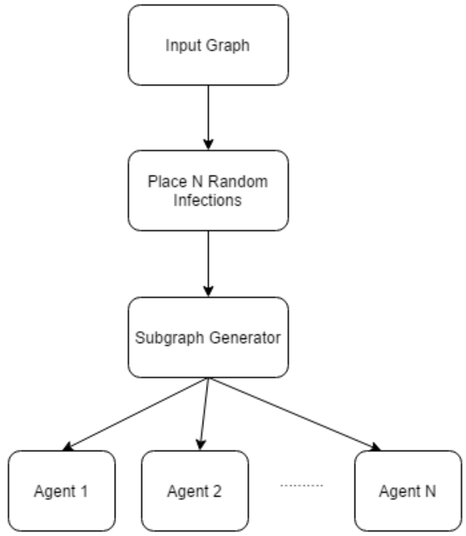



Figure 4.1: Generating agents

## 4.2 Evaluation

To evaluate our framework for resource allocation, we compare the results obtained from proposed method with results obtained from brute force method. Table 4.1 depicts the size of agent's neighborhood for different experiments which need vaccines to control infection spread. Table 4.2 and Table 4.3 holds the information of experiments conducted which has the number of agents, number of vaccines that is distributed among agents, solution (yes indicates that there exists a satisfiable solution and no indicates there exists no satisfiable solution), number of rounds in negotiation-based method (negotiation phase referred as neg and brute-force phase referred as bin after neg) and brute-force method referred as bin, time taken to find a solution (satisfiable or unsatisfiable) by negotiation-based method and brute-force method, and the difference in time between both the methods(positive value indicates negotiation-based method performed better and vice-versa).

### 4.2.1 Negotiation-based method will always find a satisfiable solution if one exists

Figure 4.2 and Figure 4.3 presents the distribution of different number vaccines among same set of agents. In both the cases, the infection spread was successfully controlled. By satisfiable solution we mean that, distribution of vaccines such that every agent is successful in

Table 4.1: Size of Agents

| EX-PID | Size |
|---|---|
| exp1 | 377 37862 3 1 2848 12393 6418 2 16422 32544 356636 310972 410414 449878 591562 |
| exp2 | 239 6409 28112 5 16036 2962 12 15596 30773 4 98031 501633 403062 2 1 3 1 |
| exp3-exp8 | 25562 1 1368 34874 998 7044 14431 26473 81371 235299 13279 508849 481899 1 583778 1 1 592945 4 1 600157 599967 1 600423 600447 |
| exp9-exp22 | 8453 11460 3 40457 2 8834 111418 34016 97065 46101 40711 1 1 571187 6 570292 598721 1 597036 600115 600276 600407 600217 600420 600478 |
| exp23-35 | 25562 1368 34874 998 7044 14431 26473 30687 102028 4127 428578 375936 538568 454523 4 587262 580846 596435 598918 599990 600156 600248 600413 600374 600445 600461 |
| exp36-42 | 10717 13478 2780 782 9770 28023 3 15 68000 23797 19507 438681 310993 550951 568398 591178 537787 574622 599114 599556 599320 1 600295 600240 600429 600476 |
| exp43-45 | 23165 2126 18795 1051 6125 18752 48145 27630 40592 259768 327327 501192 1 525179 588495 593931 592945 596360 599764 1 600262 1 599969 2 600422 600455 600469 600467 600481 1 |
| exp46 | 15876 1 2266 32264 1 7612 20445 14 39677 52438 127581 22 356945 569244 1 574113 589211 22 2 2 1 600343 599821 600367 1 600453 600474 600459 600487 600483 600487 1 600493 1 600494 |

Table 4.2: Experimental Results

| **ExpID** | **Agents** | **Vaccines** | **Solution** | **Rounds** | | | **Negotiation** | **Brute-Force** | **Difference** |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Neg | Bin after Neg | Bin | secs | secs | mins |
| exp1 | 15 | 1500 | yes | 8 | 4 | 28 | 204 | 643 | 7.3 |
| exp2 | 17 | 700 | yes | 8 | 76 | 113 | 1748 | 2323 | 9.5 |
| exp3 | 20 | 800 | yes | 10 | 46 | 73 | 1843 | 2093 | 4 |
| exp4 | 25 | 500 | no | 8 | 52 | 80 | 970 | 1186 | 3.6 |
| exp5 | 25 | 650 | no | 7 | 87 | 107 | 1461 | 1416 | -0.78 |
| exp6 | 25 | 900 | no | 8 | 108 | 130 | 2333 | 2340 | 0.12 |
| exp7 | 25 | 850 | yes | 7 | 67 | 122 | 1597 | 1882 | 4.7 |
| exp8 | 25 | 950 | yes | 5 | 53 | 106 | 834 | 2063 | 8.3 |
| exp9 | 26 | 400 | yes | 5 | 97 | 106 | 1090 | 1202 | 1.86 |
| exp10 | 26 | 450 | yes | 5 | 95 | 119 | 1199 | 1085 | -1.9 |
| exp11 | 26 | 500 | no | 7 | 98 | 116 | 1253 | 945 | -5.12 |
| exp12 | 26 | 575 | no | 4 | 101 | 122 | 1301 | 1336 | 0.5 |
| exp13 | 26 | 600 | no | 6 | 107 | 110 | 870 | 1157 | 4.7 |
| exp14 | 26 | 625 | no | 4 | 99 | 130 | 859 | 1396 | 8.9 |
| exp15 | 26 | 650 | no | 7 | 112 | 140 | 1302 | 1517 | 3.5 |
| exp16 | 26 | 675 | no | 4 | 103 | 143 | 1075 | 1573 | 8.3 |
| exp17 | 26 | 700 | no | 5 | 110 | 125 | 1027 | 1409 | 6.4 |
| exp18 | 26 | 725 | no | 4 | 105 | 126 | 960 | 1380 | 7 |
| exp19 | 26 | 750 | yes | 7 | 101 | 126 | 981 | 1696 | 11.9 |
| exp20 | 26 | 800 | yes | 5 | 119 | 113 | 2194 | 2879 | 11.4 |
| exp21 | 26 | 850 | no | 6 | 117 | 150 | 1623 | 1792 | 2.8 |
| exp22 | 26 | 900 | yes | 8 | 100 | 124 | 2640 | 2680 | 0.6 |
| exp23 | 26 | 1025 | no | 8 | 84 | 111 | 1930 | 2006 | 1.2 |
| exp24 | 26 | 1050 | no | 9 | 97 | 110 | 2578 | 2349 | -3.8 |

Table 4.3: Experimental Results

| **ExpID** | **Agents** | **Vaccines** | **Solution** | **Rounds** | | | **Negotiation** | **Brute-Force** | **Difference** |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Neg | Bin after Neg | Bin | secs | secs | mins |
| exp25 | 26 | 1075 | no | 11 | 90 | 107 | 2015 | 2050 | 0.58 |
| exp26 | 26 | 1100 | no | 11 | 82 | 112 | 2143 | 2616 | 7.8 |
| exp27 | 26 | 1125 | no | 8 | 82 | 131 | 2535 | 3380 | 14 |
| exp28 | 26 | 1150 | no | 10 | 79 | 118 | 2030 | 2574 | 9 |
| exp29 | 26 | 1300 | no | 9 | 82 | 127 | 2467 | 3603 | 18.9 |
| exp30 | 26 | 1600 | no | 9 | 98 | 130 | 2452 | 2779 | 5.4 |
| exp31 | 26 | 2000 | no | 9 | 96 | 143 | 2272 | 3067 | 13.2 |
| exp32 | 26 | 2500 | no | 10 | 110 | 146 | 2037 | 3377 | 22.3 |
| exp33 | 26 | 2850 | no | 11 | 109 | 154 | 2812 | 3779 | 16.1 |
| exp34 | 26 | 3100 | no | 11 | 117 | 152 | 2283 | 3630 | 22 |
| exp35 | 26 | 3800 | yes | 12 | 36 | 63 | 618 | 730 | 1.8 |
| exp36 | 26 | 375 | no | 8 | 57 | 103 | 1689 | 2269 | 9.6 |
| exp37 | 26 | 425 | no | 8 | 61 | 105 | 1900 | 2624 | 12 |
| exp38 | 26 | 475 | no | 10 | 95 | 115 | 2046 | 2901 | 14.2 |
| exp39 | 26 | 725 | yes | 7 | 66 | 90 | 1975 | 2260 | 4.7 |
| exp40 | 26 | 775 | yes | 8 | 83 | 99 | 1942 | 2174 | 3.8 |
| exp41 | 26 | 900 | yes | 11 | 60 | 69 | 1615 | 1751 | 2.2 |
| exp42 | 26 | 950 | yes | 6 | 65 | 81 | 1683 | 1838 | 2.5 |
| exp43 | 30 | 1100 | no | 6 | 120 | 154 | 3944 | 4443 | 8.3 |
| exp44 | 30 | 1200 | no | 6 | 132 | 173 | 3895 | 4513 | 10.2 |
| exp45 | 30 | 1350 | no | 12 | 101 | 113 | 3802 | 3864 | 1 |
| exp46 | 35 | 1100 | yes | 5 | 110 | 176 | 5673 | 6518 | 14 |

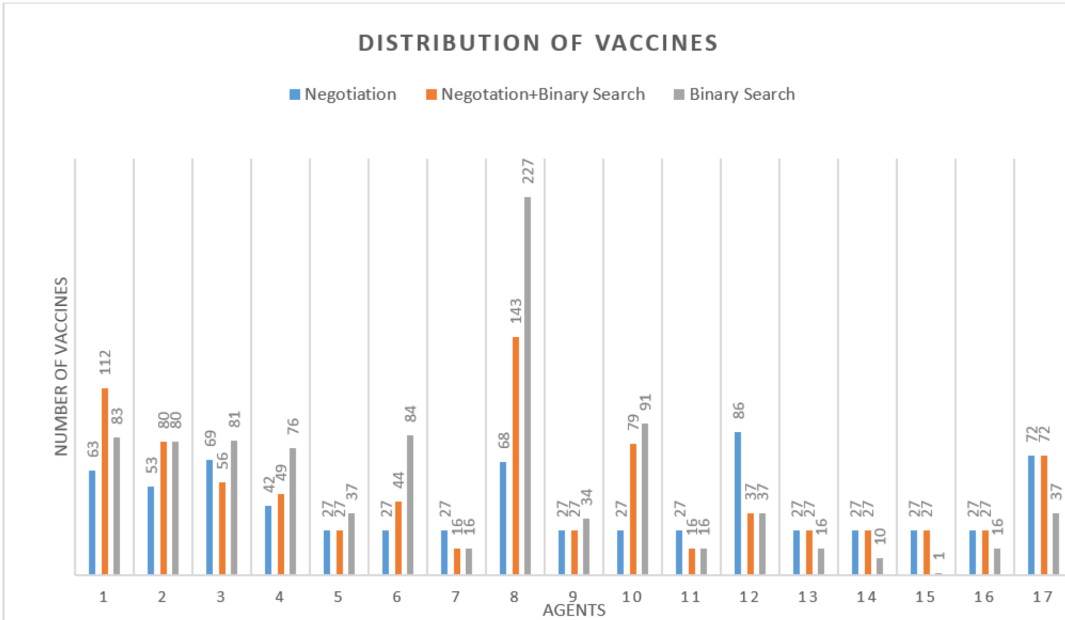



Figure 4.2: exp8: Distribution Of Vaccines. All agents are satisfied.

controlling the infection spread is found and unsatisfiable solution is when there is atleast one agent not successful in controlling infection spread with the allocation. The blue bar represents the distribution of vaccines after the negotiation round. If a satisfiable solution is not found, then brute-force method is used where agents holding extra vaccines than required to control diffusion lends to agents which unsatisfied with assignment. The orange bar represents the distribution of vaccines after negotiation round and brute-force(second round in negotiation-based method) method. The gray bar indicates the distribution of vaccines from brute-force method. Figure 4.4 depicts the distribution of vaccines on different set of agents where Infection spread is controlled. We have observed that a solution such that every agent can control the infection spread is found, if there exists one.

### 4.2.2 Negotiation-based method will always satisfy as many agents as the brute-force method will satisfy

Figure 4.5 and Figure 4.6 and Figure 4.7 shows the distribution of vaccines when there is no satisfiable solution is found. In both Figure 4.5 and Figure 4.6, Negotiation based method

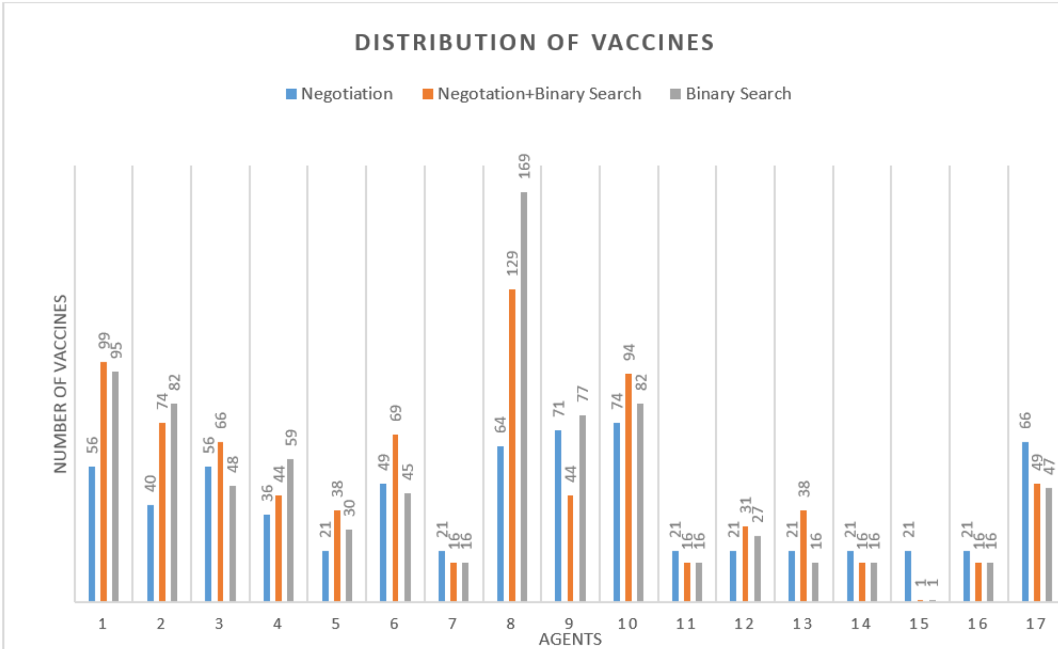



Figure 4.3: exp7: Distribution Of Vaccines. All agents are satisfied.

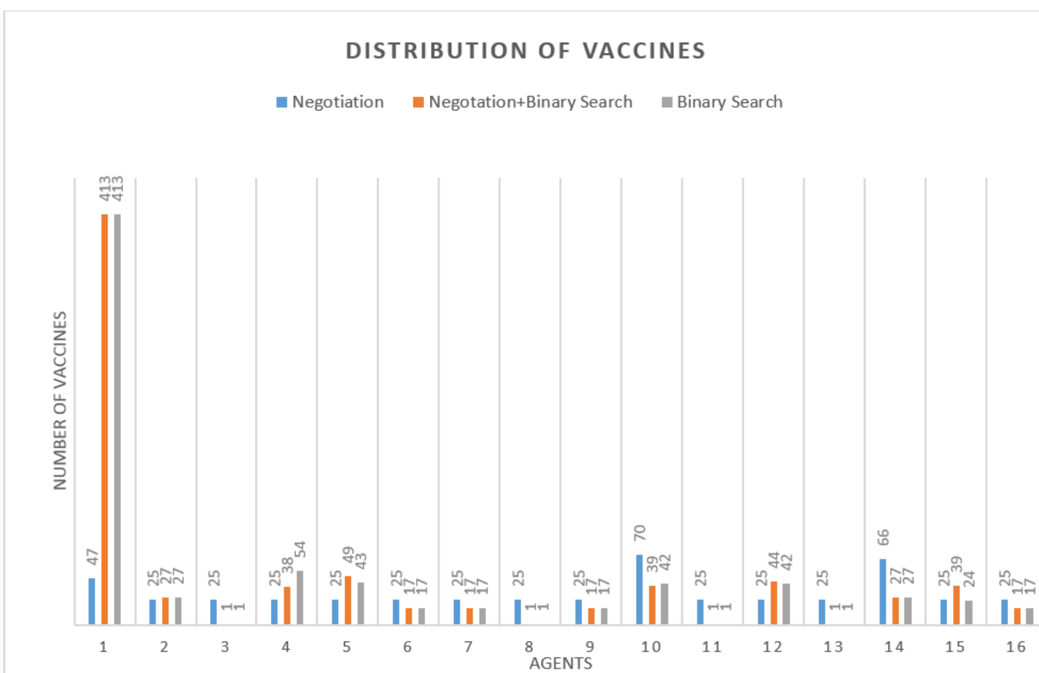



Figure 4.4: exp19: Distribution Of Vaccines. All agents are satisfied.

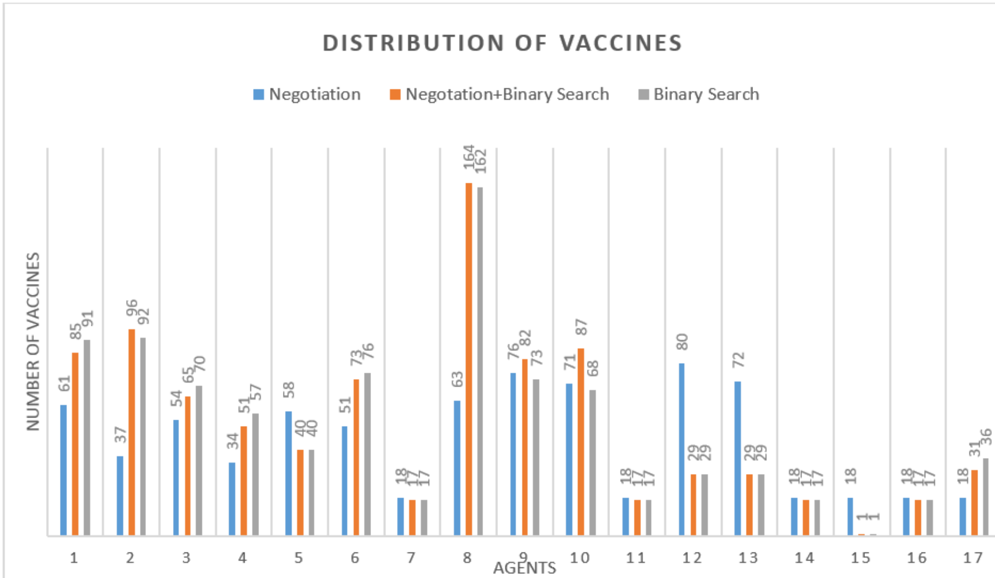



Figure 4.5: exp6: Distribution Of Vaccines. Agent 17 not satisfied and agents 10,17 not satisfied in Negotiation-based and Brute-force methods respectively.

satisfies atleast as many agents as brute-force method. But in Figure 4.7, we observe that brute-force method has larger number of agents satisfied. This observation is due to discrepancy in the responses from agents between experiments.

### 4.2.3 Negotiation-based method will converge to a solution (satisfiable or unsatisfiable) faster than brute-force method

Figure 4.8, Figure 4.9, Figure 4.10 depicts the difference of time taken by Negotiation-based method and Brute-force method over three different set of agents. Let's consider Figure 4.8, where experiment was conducted with 26 agents with different number of vaccines. In this experiment there exists a satisfiable solution with 750 vaccines. We observed that Negotiation-based method converges to a solution faster. When the difference is positive, it means that Negotiation-based method performed better than brute-force method and vice versa. There are discrepancies due to difference in the responses from agents between experiments. We have observed that Negotiation-based method will converge to a solution faster when the number of vaccines is near to the optimal vaccines (optimal solution is the number of vaccines not too

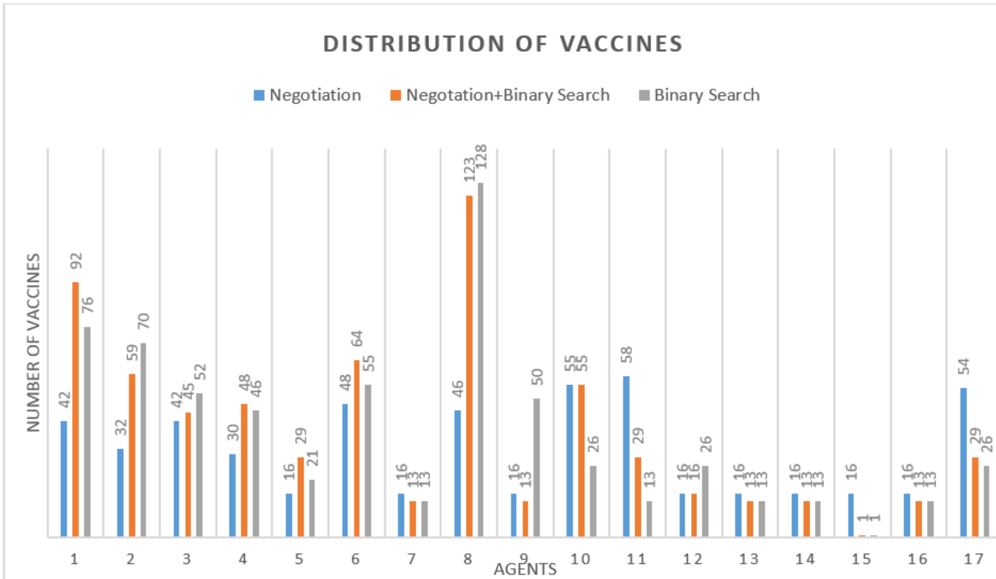



Figure 4.6: exp5: Distribution Of Vaccines. Agents 5,10,12 not satisfied and agents 9,10,12,17 not satisfied in Negotiation-based and Brute-force methods respectively.

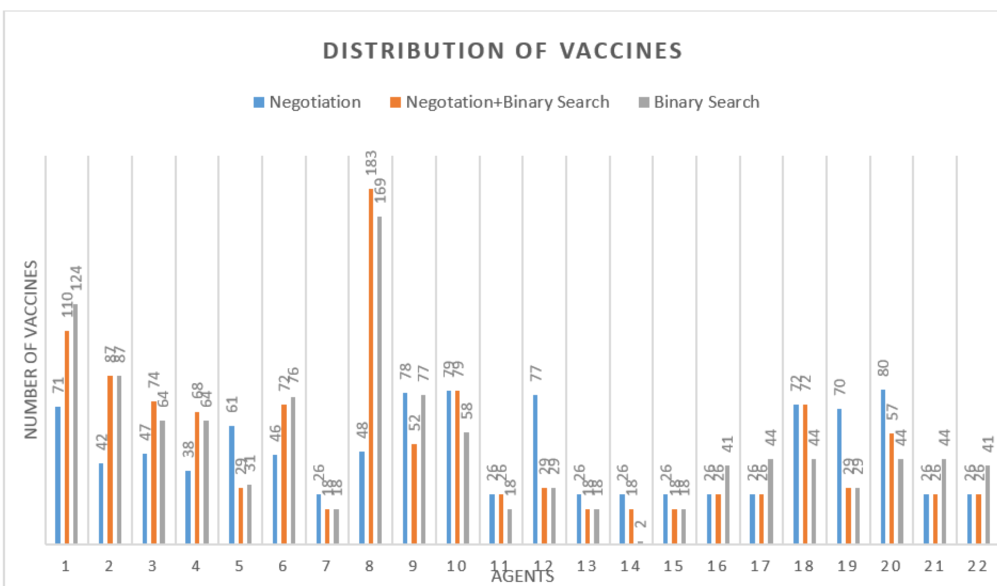



Figure 4.7: exp28: Distribution Of Vaccines. Agents 8,10,11,16,17,18,21 not satisfied and agents 10,17,18,20 not satisfied in Negotiation-based and Brute-force methods respectively.

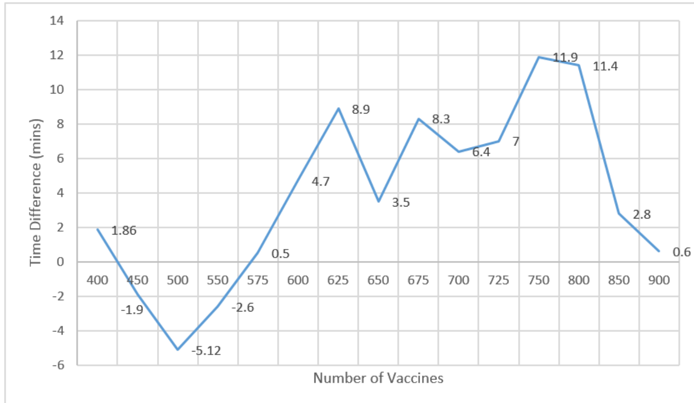



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Figure 4.8: exp9-exp22: Time-difference between Negotiation-strategy and Brute-force strategy

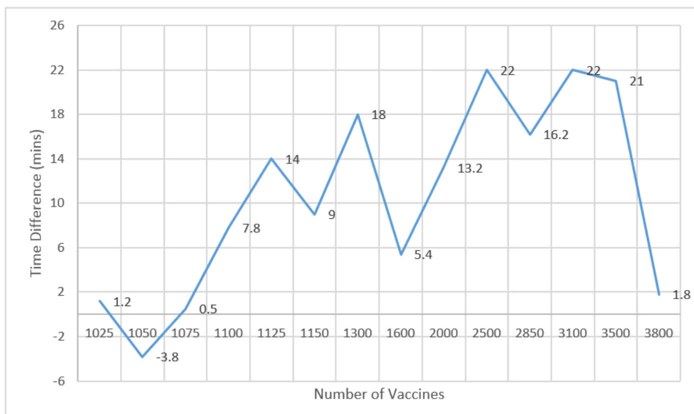


Figure 4.9: exp23-exp35: Time-difference between Negotiation-strategy and Brute-force strategy

less or not too more than required to satisfy all the participating agents).

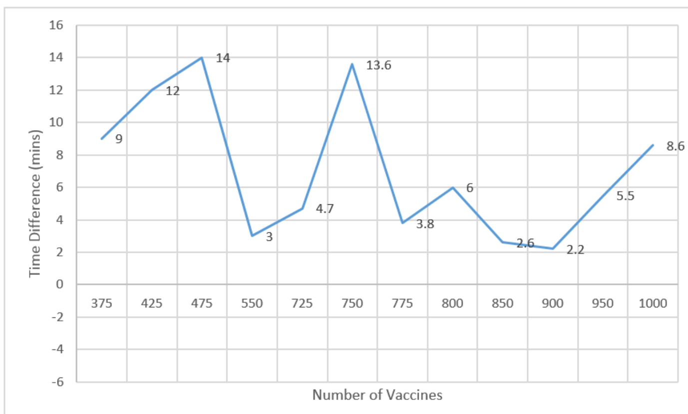


Figure 4.10: exp36-exp42: Time-difference between Negotiation-strategy and Brute-force strategy

# CHAPTER 5. CONCLUSION

## 5.1 Summary

Controlling information diffusion is an important area of research in multiple domains ranging from epidemiology, opinion propagation, firefighters to intrusion detection in networks. Due to the nature of the real-world problems, there can be multiple regions with requirement of resources to control information diffusion and resources available to prevent such diffusion are often limited. Hence we cannot establish control mechanisms a prior and it is important to devise a strategy that distributes the resources by observing the behavior of multiple networks. In this thesis, we tried to address the question; *Given the resources available and multiple agents overseeing their respective neighborhoods, can a central controller distribute the resources by sequence of interactions with agents, such that every agent can be satisfied.* We adapted a multi-agent negotiation based resource allocation framework with an objective to carefully allocate the available resources and control the information propagation in every neighborhood. We proposed an iterative negotiation protocol controlled by a central controller to allocate and reallocate the resources to multiple agents based on the partial information provided by the agents. Our framework is modular; it can be evaluated with different control strategies by agents depending on the requirements. Also we can control how much and what information an agent is willing to provide to the mediator. We have applied our technique to publicly available networks in SNAP project (Leskovec and Krevl (2014) to evaluate our framework and the results prove that our methodology is feasible in real-time. We have given few experimental observations which essentially tells us when the framework works best in comparison to brute force method.

## 5.2 Future Work

1. **Negotiating the threshold**

   There are different aspects that can be negotiated besides negotiating vaccines among agents. In the proposed framework, agents are cooperative and willing to lend excess resources held by agents to those agents in need. Therefore, mediator negotiates with the agents and reassigns the resources to agents. As a possible direction to future work, we would like to investigate on the question; *If the resources cannot be allocated in a way that can satisfy the needs of all the agents, can agents negotiate over the threshold value and reach to an approximation of satisfiability*? If yes, how can we negotiate; keeping the threshold constant, negotiate with resources, and if there exists no solution, negotiate with the threshold and repeat the process. To explain the idea of negotiating threshold, here is an instance; In field of epidemiology, let's consider the two agents to be regions A and B. In case of insufficient resources, region A might handle high threshold values because of the large number of available medical facilities. Relatively, people in region A have better access to medical facilities. With an objective to control the spread in every region, the threshold value for agent representing A can be increased and assigned fewer vaccines (resources).

2. **Vaccines per time step**

   We consider that only a fraction of total vaccines are available at one time step. Every agent, once allocated with vaccines, uses fraction of assigned vaccines at every time step and simulates to check if information propagation can be controlled. We would like to consider analyzing an open problem; *Not imposing any restriction on number of vaccines that can used by an agent per time step, instead leaving the choice of deciding on usage of given vaccines on the agent, can we devise a better strategy to allocate resources*?

3. **Non-cooperating agents**

   In proposed method, we considered the agents to be cooperative but we would like to explore the strategy when there are set of non-cooperative agents. Let's assume there are k groups of n agents where agents within a group cooperate with each other but agents do not cooperate with other agents in outside groups. The question would be on how to distribute the resources based on the information given by different groups. There will be negotiation based on information provided by agents but the truthfulness of the information cannot be validated as set of agents are non-cooperative. Also we can consider priorities among agents or group of agents where some agents might be responsible for high-risk regions than others so that groups with higher priority will have to be protected at any cost.

# BIBLIOGRAPHY


Agogino, A. and Tumer, K. (2008). Regulating air traffic flow with coupled agents. In *Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems - Volume 2*, AAMAS '08, pages 535–542.

Anderson, R. M. and May, R. M. (1979). Population biology of infectious diseases: Part i. *Nature*, 280:361–367.

Barabasi, A.-L. and Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286(5439):509–512.

Brams, S. J. and Taylor, A. D. (2000). *The win-win solution - guaranteeing fair shares to everybody.* W. W. Norton & Company.

Briesemeister, L., Lincoln, P., and Porras, P. (2003). Epidemic profiles and defense of scale-free networks. In *Proceedings of the 2003 ACM Workshop on Rapid Malcode*, WORM '03, pages 67–75.

Briola, D. and Mascardi, V. (2011). Multi agent resource allocation: a comparison of five negotiation protocols. In *WOA*, pages 95–104.

Chen, P.-A., David, M., and Kempe, D. (2010). Better vaccination strategies for better people. In *Proceedings of the 11th ACM Conference on Electronic Commerce*, EC '10, pages 179–188.

Chevaleyre, Y., Dunne, P. E., Endriss, U., Lang, J., Lemaître, M., Maudet, N., Padget, J., Phelps, S., Rodríguez-Aguilar, J. A., and Sousa, P. (2006). Issues in multiagent resource allocation. *Informatica (Slovenia)*, 30:3–31.

Cohen, R., Havlin, S., and ben Avraham, D. (2003). Efficient immunization strategies for computer networks and populations. *Phys. Rev. Lett.*, 91:247901.

Davis, R. and Smith, R. G. (1988). Distributed artificial intelligence. chapter Negotiation As a Metaphor for Distributed Problem Solving, pages 333–356.

Do, T. S. and Lee, Y. S. (2016). Modeling the spread of ebola. *Osong Public Health and Research Perspectives*, 7:43–48.

Dybiec, B., Kleczkowski, A., and Gilligan, C. A. (2004). Controlling disease spread on networks with incomplete knowledge. *Phys. Rev. E*, 70:066145.

Endriss, U., Maudet, N., Sadri, F., and Toni, F. (2011). Negotiating socially optimal allocations of resources. *CoRR*, abs/1109.6340.

Erdos, P. and Renyi, A. (1960). On the evolution of random graphs. In *PUBLICATION OF THE MATHEMATICAL INSTITUTE OF THE HUNGARIAN ACADEMY OF SCIENCES*, pages 17–61.

Eubank, S., Guclu, H., Anil Kumar, V. S., Marathe, M. V., Srinivasan, A., Toroczkai, Z., and Wang, N. (2004). Modelling disease outbreaks in realistic urban social networks. *Nature*, 429(2):180–184.

Finbow, S. and Macgillivray, G. (2007). The firefighter problem: a survey of results, directions and questions.

Gebhart, G. (2004). Worm propagation and countermeasures.

Habiba, H., Yu, Y., Berger-Wolf, T. Y., and Saia, J. (2010). Finding spread blockers in dynamic networks. In *Proceedings of the Second International Conference on Advances in Social Network Mining and Analysis*, SNAKDD'08, pages 55–76.

Hsu, S.-B. and Hsieh, Y.-H. (2005). Modeling intervention measures and severity-dependent public response during severe acute respiratory syndrome outbreak. *SIAM Journal on Applied Mathematics*, 66(2):627–647.

Keeling, M. J. and Eames, K. T. (2005). Networks and epidemic models. *Journal of the Royal Society Interface*, 393(6684):295–307.

Kimura, M., Saito, K., and Motoda, H. (2008). Minimizing the spread of contamination by blocking links in a network. In *Proceedings of the 23rd National Conference on Artificial Intelligence - Volume 2*, AAAI'08, pages 1175–1180.

Krebs, V. (2010). T n t : The network thinkers. http://www.thenetworkthinkers.com/2010/03/overlapping-networks.html. Accessed: 2017-03-20.

Kyaw, T. H., Ghosh, S., and Verbrugge, R. (2013a). Multi-player multi-issue negotiation with mediator using cp-nets. In *ICAART 2013 - Proceedings of the 5th International Conference on Agents and Artificial Intelligence, Volume 1, Barcelona, Spain, 15-18 February, 2013*, pages 99–108.

Kyaw, T. H., Ghosh, S., and Verbrugge, R. (2013b). Multi-player multi-issue negotiation with mediator using cp-nets. In *ICAART*.

Lerman, K. and Ghosh, R. (2010). Information contagion: an empirical study of the spread of news on digg and twitter social networks. *CoRR*, abs/1003.2664.

Leskovec, J. and Krevl, A. (2014). SNAP Datasets: Stanford large network dataset collection. http://snap.stanford.edu/data.

Marcelino, J. M. and Kaiser, M. (2009). Reducing influenza spreading over the airline network. *PLoS Currents*, 1.

Purwin, O., D'Andrea, R., and Lee, J.-W. (2008). Theory and implementation of path planning by negotiation for decentralized agents. *Robot. Auton. Syst.*, 56(5):422–436.

Saha, S. and Sen, S. (2007). An efficient protocol for negotiation over multiple indivisible resources. In *Proceedings of the 20th International Joint Conference on Artifical Intelligence*, IJCAI'07, pages 1494–1499.

Shafiq, M. Z., Ilyas, M. U., Liu, A. X., and Radha, H. (2013). Identifying leaders and followers in online social networks. *IEEE Journal on Selected Areas in Communications*, 31(9-Supplement):618–628.

Shakarian, P., Bhatnagar, A., Aleali, A., Shaabani, E., and Guo, R. (2015). *The Independent Cascade and Linear Threshold Models*, pages 35–48. Springer International Publishing.

Tong, H., Prakash, B. A., Eliassi-Rad, T., Faloutsos, M., and Faloutsos, C. (2012). Gelling, and melting, large graphs by edge manipulation. In *Proceedings of the 21st ACM International Conference on Information and Knowledge Management*, CIKM '12, pages 245–254.

Šišlák, D., Samek, J., and Pěchouček, M. (2008). Decentralized algorithms for collision avoidance in airspace. In *Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems - Volume 2*, AAMAS '08, pages 543–550.

Watts, D. J. and Strogatz, S. H. (1998). Collective dynamics of small-world networks. *Nature*, 393(6684):440–442.

Zhang, Y. and Prakash, B. A. (2014). *DAVA: Distributing Vaccines over Networks under Prior Information*, pages 46–54.